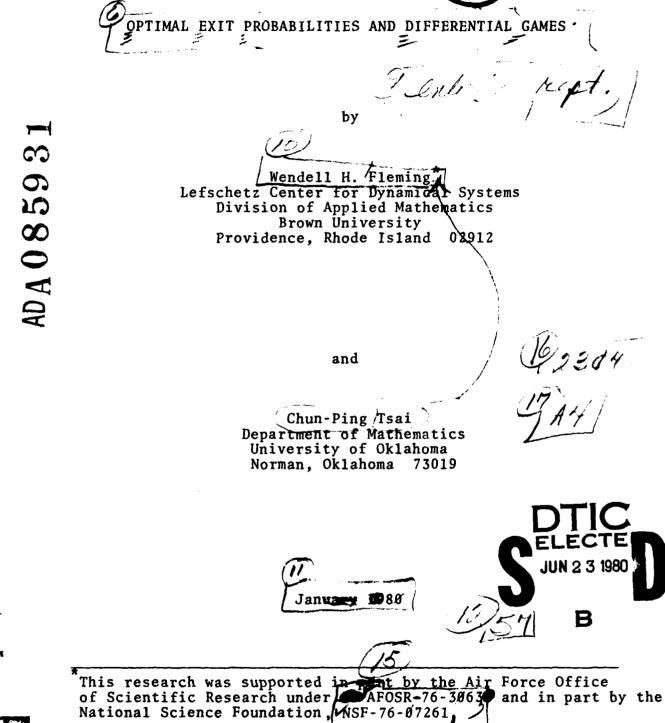


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Optimal Exit Probabilities and Differential Games

by

Wendell H. Fleming and Chun-Ping Tsai

Abstract: The problem is to control the drift of a Markov diffusion process in such a way that the probability that the process exits from a given region D during a given finite time interval is minimum. An asymptotic formula for the minimum exit probability when the process is nearly deterministic is given. This formula involves the lower value of an associated differential game. It is related to a result of Ventsel and Freidlin for nearly deterministic, uncontrolled diffusions.

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## OPTIMAL EXIT PROBABILITIES AND DIFFERENTIAL GAMES

## Wendell H. Fleming and Chun-Ping Tsai

1. <u>Introduction</u>. Let  $\xi$  be an n-dimensional stochastic process with continuous sample paths, defined for times  $t \ge 0$ . Let D be a given bounded open subset of n-dimensional  $E^n$ . If  $\xi(0) \in D$ , the exit time is the first time  $\tau$  such that  $\xi(\tau) \in \partial D$ . For fixed T > 0 the exit probability is  $P(\tau < T)$ .

In this paper, we suppose that  $\xi$  is a controlled process, which obeys the stochastic differential equation

(1.1) 
$$d\xi = b[\xi(t), y(t)]dt + \varepsilon^{1/2}dw,$$

where y(t) is a control applied at time t,  $\varepsilon > 0$  a parameter, and w(t) an n-dimensional brownian motion. We assume that  $y(t) \in Y$ , where  $Y \in E^{M}$  is a given compact set. Moreover, the control processes y admitted in (1.1) have the feedback form

$$y(t) = y(t,\xi(t))$$

where  $\underline{y}$  is any Borel measurable function from  $[0,T] \times E^n$  into Y. As initial data we have  $\xi(0) = x$ , for given vector  $x \in D$ . For general background on these concepts see [FR1, Chap. VI].

Let us denote the exit probability by  $\tau_{\underline{y}}^{\varepsilon}$ , to indicate dependence on the feedback control law  $\underline{y}$  and on  $\varepsilon$ . Let  $q_{\underline{y}}^{\varepsilon} = P(\tau_{\underline{y}}^{\varepsilon} \le T)$ . We seek a control law which minimizes the exit

probability  $q_{\underline{Y}}^{\varepsilon}$ . From the point of view of applications, this is a reasonable criterion of performance of the control system, if D is considered as a region of states in which the system operates in an "acceptable" way. The minimum exit probability is denoted by

(1.2) 
$$q^{\varepsilon} = \min_{y} q_{\underline{y}}^{\varepsilon}.$$

In §2 we shall replace the initial time 0 by any initial time s,  $0 \le s < T$ . Then  $q^{\varepsilon} = q^{\varepsilon}(s,x)$  is a function of the initial time s and initial state  $x = \xi(s)$ . The function  $q^{\varepsilon}$  satisfies the dynamic programming equation with suitable boundary conditions (see (2.4), (2.5) below). In special cases, this boundary value problem was solved numerically by Dorato and Van Melaert [DVM]. However, it is generally difficult to get effective information about  $q^{\varepsilon}$  and the optimal control law in this way. Instead, we seek an asymptotic formula for  $q^{\varepsilon}$  valid for small  $\varepsilon$ . Our main results (Theorems 4.1 and 4.2) assert that

(1.3) 
$$\lim_{\varepsilon \to 0} \varepsilon \log q^{\varepsilon} = I,$$

where I is the lower value of a certain differential game. The proofs involve some technical complications. However, two different heuristic arguments can be given to suggest the validity of (1.3). One of these is as follows (a second heuristic derivation of (1.3) based on the dynamic programming equation for  $q^{\epsilon}$  is given in §2.) Given a feedback control  $\underline{y}$  the drift coefficient in the stochastic differential equation (1.1) is

(1.4) 
$$b_{y}(t,\xi) = b(\xi,y(t,\xi)).$$

If  $b_{\chi}$  is Lipschitz, then the Ventcel-Freidlin estimates [Fr 2, Chap. 14] imply

(1.5) 
$$\lim_{\varepsilon \to 0} \varepsilon \log q_{\underline{\chi}}^{\varepsilon} = I_{\underline{\chi}},$$

(1.6) 
$$I_{\underline{Y}} = \min_{\phi \in \mathscr{F}} \frac{1}{2} \int_{0}^{T} |b_{\underline{Y}}(t, \phi(t)) - \dot{\phi}(t)|^{2} dt,$$

and where  $\mathscr{F}$  is the class of all  $\phi \in C^1([0,T];E^n)$  such that  $\phi(0) = x$  and  $\phi(\theta) \in \partial D$  for some  $\theta \in [0,T]$ . A stochastic control proof of (1.6) is given in [F4, §7]. If we set

(1.7) 
$$\dot{\phi}(t) = z(t), \quad 0 \le t \le T,$$

then we can regard z(t) as a new control associated with the minimum problem (1.6). Intuitively, minimizing  $q_{\underline{\chi}}^{\varepsilon}$  corresponds in the limit as  $\varepsilon + 0$  to choosing  $\underline{\chi}$  to maximize  $I_{\underline{\chi}}$ . This leads us to consider a differential game, described formally as follows. Let

(1.8) 
$$L(x,y,z) = \frac{1}{2} |b(x,y) - z|^2$$
.

In (1.6) we may replace the upper limit T by the first time  $\theta$  such that  $\phi(\theta) \in \partial D$ , and take  $\dot{\phi}(t) = b_{\chi}(t, \phi(t))$  for  $t > \theta$ . The integral in (1.6) is then

(1.9) 
$$\int_0^\theta L(\phi(t), y(t), z(t)) dt,$$

where  $y(t) = y(t, \phi(t))$  is chosen by the original controller and z(t) is chosen by a new second controller who knows y. The second controller then knows y(t) as well as  $\phi(t)$ .

In the formal description of the differential game,  $\phi(t)$  is the state of the game at time t, with initial data  $\phi(0) = x$ ,  $x \in D$ . The game dynamics are (1.7), subject to the restriction that  $\phi(t)$  must reach  $\partial D$  at some time  $\theta \in (0,T]$ . The original controller seeks to maximize the payoff (1.9), and the second controller seeks to minimize (1.9). Note that y(t) appears in (1.9) but not in (1.7). Thus the role of the maximizing controller is a passive one. The term "lower value" refers to the advantage in information which the minimizing controller has (see [Fr 1]).

The intuitive description above does not suffice to define rigorously a differential game with lower value I. In the rigorous treatment we shall obtain I as the limit of values of corresponding discrete-time games, following the method of [F1]. We have been unable to obtain the limit in (1.3) directly from the Ventcel-Freidlin estimates (1.5). The restriction by Lipschitz under which (1.5) is derived is too restrictive for the problem of optimal exit probability; and there is no guarantee of uniformity with respect to y of the limit in (1.5).

The outline of the paper is as follows. In §2 we introduce the function  $I^{\varepsilon} = -\varepsilon \log q^{\varepsilon}$ . Note that (1.3) asserts that  $I^{\varepsilon} + I$  as  $\varepsilon + 0$ . This logarithmic transformation changes the

dynamic programming equation for  $q^{\epsilon}$  into the nonlinear parabolic partial differential equation (2.7) for  $I^{\epsilon}$ . As  $\epsilon \to 0$ , this equation degenerates into a first-order equation, which is just the Isaacs equation for the lower value  $I^{\epsilon}$  of the differential game described intuitively above. The function  $I^{\epsilon}(s,x)$  tends to  $+\infty$  as  $s \to T$ . We introduce a penalty function method, in which  $I^{\epsilon}$  is replaced by a solution  $I^{\epsilon}_{M}$  of (2.7) with terminal data  $M\Phi(x)$  when s = T. As  $M \to \infty$ ,  $I^{\epsilon}_{M}$  increases to  $I^{\epsilon}$ . In §2 we give a priori estimates for  $I^{\epsilon}$ , based on standard estimates for brownian motion and on the maximum principle for parabolic equations.

In §3 we introduce penalized differential games, by a discretization procedure similar to [F1], [F2]. For technical reasons, we impose a bound  $|z| \le c$  for the second controller. It turns out that for sufficiently large  $c \ge c(M)$ ,  $I_M^{\varepsilon}$  is the lower value of the penalized stochastic differential game. As  $\varepsilon \to 0$ ,  $I_M^{\varepsilon} \to I_M$  where  $I_M$  is the lower value of the corresponding penalized deterministic differential game.

As  $M \to \infty$ ,  $I_M$  increases to a limit I. In §4 we show that  $I^{\varepsilon} \to I$  as  $\varepsilon \to 0$ , and identify I as the lower value of the differential game described formally above.

2. <u>Preliminary Results</u>. We make the following assumptions throughout the paper. D is a bounded, open subset of  $E^n$ , with boundary  $\partial D$  a manifold of class  $C^3$ . The control space Y is a compact subset of  $E^n$ . We consider times in the interval [0,T]. The vector function b in (1.1) is of class  $C^1(E^n \times Y; E^n)$ .

Moreover, for some constants  $B_1, B_2$ 

$$|b(x,y)| \le B_1,$$
  
 $|b(x,y) - b(\overline{x},y)| \le B_2|x-\overline{x}|.$ 

This is actually no restriction since b is  $C^1$  and we stop the solution  $\xi$  to (1.1) when  $\xi(t)$  leaves the bounded set D or when t = T. The function L in (1.8) then satisfies

$$|L(x,y,z) - L(\overline{x},y,z)| \leq \Lambda(1+|z|)|x-\overline{x}|.$$

(2.2) 
$$c_1 |z|^2 - c_2 \le L$$
,

for some constants  $\Lambda$ ,  $c_1 > 0$ ,  $c_2$ .

Let  $\mathscr{Y}$  be the class of Borel measurable functions  $\underline{y}$  from  $[0,T]\times E^n$  into Y. For a feedback control law  $\underline{y}\in\mathscr{Y}$ , the stochastic differential equations (1.1) take the form

(2.3) 
$$d\xi = b_{\chi}(t,\xi(t))dt + \varepsilon^{1/2}dw$$

with  $b_{\underline{y}}$  as in (1.4). We consider (2.3) with initial data  $\xi(s) = x$ , where  $0 \le s < T$ ,  $x \in D$ . (Later, we specialize by taking s = 0.) This is a problem of completely observed controlled diffusions [FR1, Chap. VI]. However, instead of the kind of performance criterion considered in [FR1] we wish to minimize the exit probability

$$q_{\underline{Y}}^{\varepsilon}(s,x) = P(\tau_{\underline{Y}}^{\varepsilon} \leq T),$$

with  $\tau_{\underline{Y}}^{\varepsilon}$  the first time t > s such that  $\xi(t) \in \partial D$ . Let

Q = (0,T) × D, 
$$\overline{Q}$$
 = [0,T] ×  $\overline{D}$ ,  $\overline{Q}_0$  =  $\overline{Q}$  - {T} ×  $\partial D$ .

Given  $A \subset E^{n+1}$  and  $0 < \beta \le 1$  we say that a function q(s,x) has finite  $\beta$ -norm on A if there exists a constant K such that

$$|q(s,x) - q(s',x')| \le K(|x-x'|^{\beta} + |s-s'|^{\beta/2})$$

for all (s,x),  $(s',x') \in A$ . We say that  $q \in C^0_\beta, ^1(A)$  if q and the gradient  $q_x$  in the variables  $x = (x^1, \ldots, x^n)$  have finite  $\beta$ -norm on A. If  $q,q_x,q_s, q_{x^ix^j}, i, j = 1,\ldots,n$  have finite  $\beta$ -norm on A, then we say that  $q \in C^{1,2}_\beta(A)$ .

The minimum exit probability  $q^{\epsilon}(s,x)$  belongs to  $C_{\beta}^{1,2}(A)$  for any compact  $A \subset \overline{\mathbb{Q}}_0$  and  $\beta \in (0,1)$ . Moreover, in  $\overline{\mathbb{Q}}_0$  the following dynamic programming equation holds:

(2.4) 
$$0 = q_s^{\varepsilon} + \frac{\varepsilon}{2} \Delta_x q^{\varepsilon} + \min_{y \in Y} q_x^{\varepsilon} \cdot b(x,y),$$

where  $\Delta_{\rm X}$  is the Laplacean. See [FR1, p. 161], also the Remark below. The boundary data are

(2.5) 
$$q^{\varepsilon}(s,x) = 1$$
 for  $s < T$ ,  $x \in \partial D$ ;  $q^{\varepsilon}(T,x) = 0$ ,  $x \in D$ .

Let

(2.6) 
$$I^{\varepsilon}(s,x) = -\varepsilon \log q^{\varepsilon}(s,x).$$

By elementary calculus  $I^{\varepsilon}$  satisfies the nonlinear parabolic partial differential equation

(2.7) 
$$0 = I_S + \frac{\varepsilon}{2} \Delta_x I^{\varepsilon} + H(x, I_x^{\varepsilon}),$$

(2.8) 
$$H(x,p) = -\frac{1}{2} |p|^2 + \max_{y \in Y} p \cdot b(x,y).$$

Here  $p = (p_1, ..., p_n)$  denotes a row vector. From (2.5) the boundary data are

(2.9) 
$$I^{\varepsilon}(s,x) = 0$$
 for  $s < T$ ,  $x \in \partial D$ ;  $I^{\varepsilon}(T,x) = +\infty$ ,  $x \in D$ .

The function L in (1.8) is strictly convex and quadratic as a function of z. The function dual to L, in the sense of duality for concave and convex functions, is

(2.10) 
$$H(x,y,p) = \min_{z} [L(x,y,z) + p \cdot z],$$

where the  $\min$  is over all  $z \in E^n$ . An easy calculation shows that

$$H(x,y,p) = -\frac{1}{2}|p|^2 + p \cdot b(x,y),$$

and therefore by (2.8), (2.10)

(2.11) 
$$H(x,p) = \max \min_{y \in Y} [L(x,y,z) + p \cdot z].$$

Equation (2.7) then takes the form

(2.7') 
$$0 = I_{S}^{\varepsilon} + \frac{\varepsilon}{2} \Delta_{X} I^{\varepsilon} + \max_{y \in Y} \min_{z} [L(x,y,z) + I_{X}^{\varepsilon} \cdot z].$$

This is the dynamic programming equation associated with a stochastic differential game. Similar equations were considered in [F2]. When  $\varepsilon = 0$ , (2.7') reduces to a first order partial differential equation, which is the Isaacs equation for the non-stochastic differential game described formally in §1. This provides a second heuristic argument for considering this differential game, in addition to the heuristic argument given in §1.

We shall approximate the infinite terminal condition  $I^{\varepsilon}(T,x) = +\infty$  by a large, but finite, terminal condition as follows. Let  $\Phi(x)$  be a function of class  $C^{2}(\overline{D})$  satisfying

(2.12) 
$$\gamma_1 \operatorname{dist}(x, \partial D) \le \Phi(x) \le \gamma_2 \operatorname{dist}(x, \partial D)$$
 for  $x \in D$   

$$\Phi(x) = 0 \quad \text{for} \quad x \notin D,$$

where  $\gamma_1, \gamma_2$  are positive constants and dist(x,  $\partial D$ ) is the distance between a point x and the boundary  $\partial D$ . For each M > 0 let

(2.13) 
$$q_{M}^{\varepsilon}(s,x) = \min_{\Sigma} E \exp\left\{-\frac{M\phi\left[\xi\left(\tau_{Y}^{\varepsilon}\Lambda T\right)\right]}{\varepsilon}\right\}$$

where as before  $\xi$  satisfies (2.3) with initial data  $\xi(s) = x$  and  $\tau_{\underline{Y}}^{\varepsilon} \wedge T = \min[\tau_{\underline{Y}}^{\varepsilon}, T]$ . The minimum is taken among all feedback controls  $\underline{Y} \in \mathscr{Y}$ . This is a stochastic control problem of the kind considered in [FR1, Chap VI, §4,6]. According to results given there,  $q_{\underline{M}}^{\varepsilon}$  satisfies the dynamic programming equation (2.4). The function  $q_{\underline{M}}^{\varepsilon}$  belongs to  $C_{\beta}^{0,1}(\overline{Q}) \cap C_{\beta}^{1,2}(A)$  for any compact  $A \subset \overline{Q}_0$  and  $\beta \in (0,1)$ . Moreover,  $q_{\underline{M}}^{\varepsilon}(s,x)$  is also the minimum of the expectation in (2.13), taken among nonanticipative Y-valued control processes [FR1, pp. 162-163].

Remark. By estimates for parabolic equations, and the fact that  $q_M^\varepsilon$  is uniformly bounded, the partial derivatives  $(q_M^\varepsilon)_s, (q_M^\varepsilon)_{x^i}, (q_M^\varepsilon)_{x^i x^j}$  satisfy Hölder conditions on any compact subset of  $\overline{\mathbb{Q}}_0$  which are uniform with respect to M for fixed  $\varepsilon > 0$ . See [LSU], also [FR1, Appendix E]. The boundary data are

$$q_{M}^{\varepsilon}(s,x) = 1$$
, for  $s < T$ ,  $x \in \partial D$ ;  $q_{M}^{\varepsilon}(T,x) = \exp\left[-\frac{M\Phi(x)}{\varepsilon}\right]$ ,  $x \in D$ .

Moreover,  $0 < q_{M+1}^{\varepsilon} \le q_M^{\varepsilon} < 1$ . The limit  $\tilde{q}^{\varepsilon}(s,x)$  of  $q_M^{\varepsilon}(s,x)$  as  $M \to \infty$  is a solution of (2.4) belonging to  $C_{\beta}^{1,2}(A)$  for any compact  $A \subset \overline{\mathbb{Q}}_0$ . Moreover,  $\tilde{q}^{\varepsilon}$  has the boundary data (2.5). A Verification Theorem [FR1, p. 159] implies that  $\tilde{q}^{\varepsilon} = q^{\varepsilon}$  and that  $q^{\varepsilon}(s,x)$  is the minimum exit probability. Actually, the proof of the Verification Theorem in [FR1] must be modified slightly since

 $q^{\varepsilon}$  is discontinuous at points (T,x),  $x \in \partial D$ . This causes no difficulty, since the random variable  $\xi(T)$  is absolutely continuous with respect to Lebesgue measure in  $E^{n}$ . Hence

$$P(\tau^{\varepsilon} = T) \le P(\xi(T) \in \partial D) = 0.$$

Let

(2.14) 
$$I_{M}^{\varepsilon}(s,x) = -\varepsilon \log q_{M}^{\varepsilon}(s,x).$$

Since  $q_M^{\varepsilon} \ge q^{\varepsilon}$ , and  $q_M^{\varepsilon} + q^{\varepsilon}$  as  $M \to \infty$ ,

$$(2.15) I_{M}^{\varepsilon} \leq I^{\varepsilon}, I_{M}^{\varepsilon} \uparrow I^{\varepsilon} as M \rightarrow \infty.$$

Moreover,  $I_M^{\varepsilon}$  is a solution of (2.7) (or equivalently (2.7')) with the boundary data

$$(2.9_M)$$
  $I_M^{\varepsilon}(s,x) = 0$  for  $s < T$ ,  $x \in \partial D$ ;  $I_M^{\varepsilon}(T,x) = M\Phi(x)$ ,  $x \in D$ .

Let us now give some bounds for  $I^{\varepsilon}$  and  $I^{\varepsilon}_{M}$ . In these lemmas we write  $I^{\varepsilon}(s,x;T)$ ,  $I^{\varepsilon}_{M}(s,x;T)$  to emphasize dependence on the final time T. Since H(x,p) does not depend on time, we have

(2.16) 
$$I^{\varepsilon}(s,x;T) = I^{\varepsilon}(0,x;T-s), I^{\varepsilon}_{M}(s,x;T) = I^{\varepsilon}_{M}(0,x;T-s).$$

Lemma 2.1. Let T' < T. There exists U such that  $I^{\epsilon}(s,x;T) \leq U$  for  $0 \leq s \leq T'$ ,  $x \in D$ , and for small  $\epsilon$ . The

constant U depends on upper and lower bounds for T - T', but not on  $\epsilon$ .

<u>Proof.</u> By (2.16) we may take s = 0 and impose the bounds  $0 < k \le T \le K$ . Since  $|b| \le B_1$ , (2.3) implies

$$\xi^{1}(T) - x^{1} \geq B_{1}^{T} + \varepsilon^{1/2}(w^{1}(T) - w^{1}(0))$$

where  $x^1$  is the first component of x etc. Since D is bounded, there exists a constant a such that  $\xi^1(T) - x^1 \ge a$  implies  $\tau_y^\varepsilon \le T$ . Hence

$$P(T^{-1/2}w^{1}(T) \geq (\varepsilon T)^{-1/2}(a+B_{1}T)) \leq P(\tau_{\underline{Y}}^{\varepsilon} \leq T) = q_{\underline{Y}}^{\varepsilon}.$$

Since  $T^{-1/2}w^1(T)$  has a standard normal distribution, we have [Fe1, p. 166]

$$\lim_{\lambda \to \infty} \lambda^{-2} \log P(T^{-1/2} w^{1}(T) \ge \lambda) = -\frac{1}{2}.$$

Hence, for small & we have for all y

$$-\varepsilon \log q_y^{\varepsilon} \leq \frac{(a+B_1T)^2}{T}$$
.

By (1.2),  $I^{\varepsilon} = -\varepsilon \log q^{\varepsilon}$  satisfies the same inequality. In Lemma 2.1 let  $U = k^{-1} (a+B_1 K)^2$ .

Lemma 2.2. Let T' < T. There exists a positive constant  $M_0$  (depending on T' but not on  $\varepsilon$ ) such that  $I^{\varepsilon}(s,x;T) \le M_0 \operatorname{dist}(x,\partial D)$  for  $0 \le s \le T'$  and for small  $\varepsilon$ .

<u>Proof.</u> By Lemma 2.1 it suffices to verify such an estimate in a neighborhood of any  $x_1 \in \partial D$ . Let  $z_1$  be the exterior unit normal to  $\partial D$  at  $x_1$ ; and let

$$D_1 = \{x \in D: dist(x,x_1) < \rho\}$$

where  $\rho$  is to be chosen later. By (2.7')

$$I_s^{\varepsilon} + \frac{\varepsilon}{2} \Delta_x I^{\varepsilon} + \max_{y \in Y} L(x,y,z_1) + I_x^{\varepsilon} \cdot z_1 \ge 0.$$

The maximum occurs at some  $\underline{y}^*(s,x)$ , measurable in (s,x) [FR1, p. 199].

Choose any  $T'' \in (T',T)$ . For s < T'',  $x \in D$ , define the process  $\psi$  by

$$d\psi = z_1 dt + \varepsilon^{1/2} dw$$
,  $\psi(s) = x$ .

Let  $\theta^{\epsilon} = \min\{T'', \text{ exit time of } \psi(t) \text{ from D}\}.$ From Itô's formula

$$I^{\varepsilon}(s,x;T) \leq E \int_{s}^{\theta^{\varepsilon}} L(\psi(t),\underline{y}^{\star},z_{1})dt + I^{\varepsilon}(\theta^{\varepsilon},\psi(\theta^{\varepsilon});T)$$

where  $y^* = \underline{y}^*(t, \psi(t))$ . Moreover,  $I^{\epsilon}(T'', x; T) \leq U$  by Lemma 2.1,

and  $I^{\varepsilon}(s,x;T) = 0$  for  $x \in \partial D$ . Since  $L(x,y^*,z_1)$  is bounded by some  $C^*$ 

$$I^{\varepsilon}(s,x;T) \leq C^{*}E(\theta^{\varepsilon}-s) + UP(\theta^{\varepsilon}=T''),$$

$$P(\theta^{\varepsilon}=T'') = P(\theta^{\varepsilon}-s\geq T''-s) \leq (T''-s)^{-1}E(\theta^{\varepsilon}-s).$$

To prove Lemma 2.2 it then suffices to show that

(2.17) 
$$E(\theta^{\varepsilon}-s) \leq C \operatorname{dist}(x, \partial D)$$

for  $x \in D_1$ ,  $0 \le s \le T'$ . This is done as in proving [F3, Lemma 4.2], as follows.

Let  $\theta_1^{\epsilon} = \min(T'', \text{ exit time of } \psi(t) \text{ from } D_1)$ , and

$$g^{\varepsilon}(s,x) = E(\theta^{\varepsilon}-s), g_{1}(s,x) = E(\theta_{1}^{\varepsilon}-s).$$

Then  $g^{\epsilon}, g_1^{\epsilon}$  both satisfy the parabolic equation

(2.18) 
$$u_s + \frac{\varepsilon}{2} \Delta_x u + u_x \cdot z_1 + 1 = 0$$

in  $[0,T") \times D_1$  with  $g^{\varepsilon} = g_1^{\varepsilon} = 0$  for  $x \in \partial D$  or s = T". For  $x \in \partial D_1 - \partial D$ ,  $g_1^{\varepsilon} = 0$ ,  $0 \le g^{\varepsilon} \le T$ .

$$\phi(t) = x + z_1(t-s)$$

and  $\theta^0$  the exit time of  $\phi(t)$  from D. We choose  $\rho < \frac{1}{2} (T-T'') \text{ and small enough that } \theta^0 - s \le 2 \text{ dist}(x,\partial D) \text{ for all } x \in D_1.$  The function  $g^0(s,x) = \theta^0 - s$  satisfies in  $[0,T'') \times D_1$  the first order equation

(2.19) 
$$g_s^0 + g_x^0 \cdot z_1 + 1 = 0,$$

with  $g^0=0$  for  $x\in\partial D$  and  $g^0\geq 0$  for  $x\in\partial D_1-\partial D$  or s=T''. Let  $\mu>0$  and  $g=(1+\mu)g^0$ . By (2.18) and (2.19), for small  $\epsilon$ 

$$g_s + \frac{\varepsilon}{2} \Delta_x g + g_x \cdot z_1 + 1 \leq 0$$
.

Hence, by the maximum principle for parabolic equations  $g_1^{\varepsilon} \le g$  on  $[0,T''] \times D_1$ . By Itô's formula

$$g^{\epsilon}(s,x) = E \int_{s}^{\theta_{1}^{\epsilon}} dt + Eg^{\epsilon}(\theta_{1}^{\epsilon}, \psi(\theta_{1}^{\epsilon})).$$

Since the first term on the right is  $g_1^{\varepsilon}(s,x)$  and  $g^{\varepsilon} \leq T$ ,

$$(2.20) g^{\varepsilon}(s,x) \leq g(s,x) + TP(\psi(\theta_1^{\varepsilon}) \in \partial D_1 - \partial D).$$

By reasoning as in [F4, p. 488], for  $s \le T'$ ,  $x \in D_1$ 

$$P(\psi(\theta_1^{\varepsilon}) \in \partial D - \partial D_1) \leq \varepsilon Bg_1^{\varepsilon}(s,x)$$

for some B. Since  $g_1^{\varepsilon} \le g_1^{\varepsilon}$  (2.20) implies

$$g^{\varepsilon}(s,x) \leq \frac{1+\mu}{1-\varepsilon BT} g^{0}(s,x) \leq \frac{2(1+\mu)}{1-\varepsilon BT} \operatorname{dist}(x,\partial D).$$

For small  $\varepsilon$ , we then have (2.17) with  $C = 3(1+\mu)$ . This proves Lemma 2.2.

Lemma 2.3. For T' < T, there exists a constant  $M_1$  such that  $I^{\varepsilon}(s,x;T) \leq I_{M}^{\varepsilon}(s,x;T')$  for all  $M \geq M_1$ ,  $0 \leq s \leq T'$ ,  $x \in D$ , and for small  $\varepsilon$ .

Proof. Both  $I^{\epsilon}(s,x;T)$  and  $I^{\epsilon}_{M}(s,x;T')$  satisfy (2.7). By Lemma 2.2, for small  $\epsilon$ 

$$I^{\varepsilon}(T';x,T) \leq M_0 dist(x,\partial D),$$

and by (2.12)

$$I_{M}^{\varepsilon}(T',x;T') = M\phi(x) \ge M\gamma_{1}dist(x,\partial D).$$

For  $x \in \partial D$ ,  $I^{\varepsilon} = I_{M}^{\varepsilon} = 0$ . Let  $M_{1} = M_{0}\gamma_{1}^{-1}$ . By the maximum principle for parabolic equations,  $I^{\varepsilon} \leq I_{M}^{\varepsilon}$  in the cylinder  $Q' = (0,T') \times D$  for any  $M \geq M_{1}$ . This proves Lemma 2.3.

The minimum in (2.11) is taken among all  $z \in E^n$ . For technical reasons we wish to consider equations corresponding to (2.7) when bounds are imposed on |z|.

For  $c \ge 1$  let

$$Z^{c} = \{z \in E^{n}: |z| < c\}.$$

Let  $I_{Mc}^{\varepsilon}$  be the solution in Q of

$$(2.21) \qquad (I_{Mc}^{\varepsilon})_{s} + \frac{\varepsilon}{2} \Delta_{x} I_{Mc}^{\varepsilon} + H^{c}(x, (I_{Mc}^{\varepsilon})_{x}) = 0,$$

(2.22) 
$$H^{C}(x,p) = \max_{y \in Y} \min_{z \in Z^{C}} [L(x,y,z) + p \cdot z]$$

with the same boundary data  $(2.9_M)$  as for  $I_M^{\varepsilon}$ . The solution  $I_{MC}^{\varepsilon}$  belongs to  $C_{\beta}^{0,1}(\overline{\mathbb{Q}}) \cap C_{\beta}^{1,2}(A)$  for any compact  $A \subset \overline{\mathbb{Q}}_0$  and  $\beta \in (0,1)$ . Since  $H^C \geq H$ , we always have  $I_{MC}^{\varepsilon} \geq I_M^{\varepsilon}$ . In section 3 we will show that for c large enough  $(c \geq c(M))$ ,  $I_M^{\varepsilon} = I_{MC}^{\varepsilon}$ . See (3.15).

Lemma 2.4. There exists a constant B = B(M) such that  $I_{MC}^{\varepsilon}(s,x) \leq B \operatorname{dist}(x,\partial D)$ , for all  $(s,x) \in Q$  and for small  $\varepsilon$ .

<u>Proof.</u> Since  $\partial D$  is of class  $C^3$ , D has the exterior sphere property. Following [F5, p. 275], given  $x_1 \in \partial D$  let A be an n-dimensional spherical ball with center  $x_2$ , radius  $|x_1-x_2|$  intersecting  $\overline{D}$  in the single point  $x_1$ . Let  $\Psi(x) = |x-x_2| - |x_1-x_2|$  and let  $\underline{z}(x) = -\Psi_X(x)$ . For small  $\varepsilon$ 

$$\frac{\varepsilon}{2} \Delta_{\mathbf{X}} \Psi + \underline{\mathbf{z}} \cdot \Psi_{\mathbf{X}} \leq -\frac{1}{2}$$

for all  $x \in D$ . As in the proof of Lemma 2.2 the function  $J^{\varepsilon} = I_{MC}^{\varepsilon}$  satisfies

$$J_s + \frac{\varepsilon}{2} \Delta_x J^{\varepsilon} + J_x^{\varepsilon} \cdot \underline{z} + L^{\star}(x) \geq 0$$
,

$$L^*(x) = \max_{y \in Y} L(x,y,\underline{z}(x)).$$

Moreover,  $L^*(x) \le L_1$ , for some  $L_1$ . For  $B \ge 2L_1$ 

$$(B\Psi - J^{\varepsilon})_{s} + \frac{\varepsilon}{2} \Delta_{x}(B\Psi - J^{\varepsilon}) + (B\Psi - J^{\varepsilon})_{x} \cdot \underline{z} \leq 0.$$

For  $x \in \partial D$ ,  $B\Psi(x) - J^{\varepsilon}(s,x) = B\Psi(x) \ge 0$ . For  $B \ge B(M) \ge 2L_1$  we have

$$B\Psi(x) - J^{\epsilon}(T,x) = B\Psi(x) - M\Phi(x) \ge 0$$
,

for all  $x \in D$ . The maximum principle for parabolic equations implies BY -  $J^{\epsilon} \ge 0$  in Q.

Given  $x \in D$ , let  $x_1$  be a point of  $\partial D$  nearest x. Then  $dist(x, \partial D) = \Psi(x)$ , which implies Lemma 2.4.

3. Penalized Differential Games. In the differential game formally described in §1, the minimizing controller is required to bring the game state  $\phi(t)$  to  $\partial D$  by some time  $\theta < T$ . We

now omit that restriction and instead impose a penalty if  $\partial D$  is not reached. Let us begin by describing formally the penalized differential game, and the corresponding penalized stochastic differential game for  $\varepsilon > 0$ . The penalized game has the same dynamics (1.7) as before, but instead of (1.9) the payoff is

(3.1) 
$$\int_0^\theta L[\phi(t),y(t),z(t)]dt + M\phi[\phi(\theta)],$$

where now  $\theta = \min\{T, \text{ exit time of } \phi(t) \text{ from } D\}$ . The penalty  $M\phi(\theta) = 0$  if  $\theta < T$  by (2.12). For  $\varepsilon > 0$  the game state  $\psi(t)$  obeys a white-noise perturbation of (1.7):

$$d\Psi = z(t)dt + \varepsilon^{1/2}dw$$
.

The payoff is

(3.2) 
$$E\left\{ \int_{0}^{\theta} L[\psi(t),y(t),z(t)]dt + M\Phi[\psi(\theta^{\epsilon})] \right\},$$

with  $\theta^{\varepsilon}=\min\{T,\ exit\ time\ of\ \psi(t)\ from\ D\}$ . For technical reasons, we impose a bound  $|z(t)|\leq c$  for the minimizing controller. Moreover, we replace the initial time 0 in (3.1) or (3.2) by any initial time  $s\in[0,T]$ , and consider the initial data  $\phi(s)=\psi(s)=x$ . The Isaac's equation for the penalized stochastic differential game is (2.21); for the deterministic game the Isaac's equation is the first-order equation corresponding to (2.21) when  $\varepsilon=0$ . We shall show below that  $I_{MC}^{\varepsilon}$  is the lower value (in a suitably defined sense) of the penalized stochastic

differential game and that its limit  $I_{Mc}^{\varepsilon}$  as  $\varepsilon \to 0$  is the lower value of the penalized deterministic game. We also show that  $I_{Mc}^{\varepsilon} = I_{M}^{\varepsilon}$  for large enough  $c \ge c(M)$ .

In order to treat these games on a rigorous basis, we discretize the game dynamics and payoff in the same way as [F1], [F2]. A somewhat different discretization procedure was used in [Fr1].

In the discussion to follow we fix M,c, and T. For N = 1,2,... let

$$\delta = \frac{T}{N}$$
,  $t_k = \frac{(k-1)T}{N}$ ,  $k = 1, ..., N + 1$ .

For simplicity we do not indicate the dependence of  $\delta$  and  $t_k$  on N. Let  $n_k^i$ ,  $k=1,\ldots,N$ ,  $i=1,\ldots,n$ , be mutually random variables which assume the values 1 and -1 each with probability  $\frac{1}{2}$ . In order to avoid certain analytical questions of integrability and the existence of a value, we shall arrange that each of these games is finite. Let

$$Y_1 \subset Y_2 \subset \ldots \subset Y$$
,  $Z_1 \subset Z_2 \subset \ldots \subset E^n$ ,

where  $Y_N, Z_N$  are finite sets for each N, the union of the sets  $Y_N$  is dense in Y, and the union of the sets  $Z_N$  is dense in  $E^N$ . For  $c \ge 1$  let

$$z^{c} = \{z: |z| \le c\}, \quad z_{N}^{c} = z^{c} \cap z_{N}.$$

We shall define for initial data (s,x) with  $s=t_{\ell}$ ,  $\ell=1,\ldots,N, \ x\in D$ , a game with  $2(N-\ell+1)$  moves. At move 2k-1, the first controller chooses some  $y_k\in Y_N$ , and at move 2k the second controller chooses some  $z_k\in Z_N^C$ ,  $k=\ell,\ldots,N$ . Both choices are obtained using strategies, as described below. The state  $\psi_{k+1}$  after move 2k is determined from the system of difference equations

(3.3) 
$$\psi_{k+1} = \psi_k + \delta z_k + \delta^{1/2} \epsilon^{1/2} \eta_k, \quad \psi_{\ell} = x.$$

At each move 2k-1 or 2k the controllers know all previous moves and also  $n_{\ell},\ldots,n_{k-1}$ . The game stops at the first step  $F^{\epsilon}$  when either  $\psi_{F^{\epsilon}+1} \notin D$  or  $F^{\epsilon}=N$ . We call  $t_{F^{\epsilon}}=(F^{\epsilon}-1)\delta$  the exit time for  $\psi_{k}$ . After play stops, the first controller receives the payoff

(3.4) 
$$\pi^{\varepsilon}(s,x) = E\left\{ \sum_{k=\ell}^{F^{\varepsilon}} \delta L(\psi_k, y_k, z_k) + M\Phi(\psi_{F^{\varepsilon}+1}) \right\}.$$

When  $\varepsilon$  = 0 we consider the corresponding deterministic game whose states  $\phi_k$  obey

(3.5) 
$$\phi_{k+1} = \phi_k + \delta z_k, \quad \phi_{\ell} = x,$$

with payoff

(3.6) 
$$\pi(s,x) = \sum_{k=0}^{F} \delta L(\phi_k, y_k, z_k) + M\phi(\phi_{F+1})$$

where  $t_F$  is the exit time for  $\phi_k$ .

The game is described more precisely by introducing the idea of strategy (also called a  $\delta$ -strategy). For the deterministic game a strategy for the first controller is the (N-l+1)-vector  $\Gamma = (\Gamma^{\ell}, ..., \Gamma^{N})$  such that  $\Gamma^{\ell}$  is any point  $y_{\ell} \in Y_{N}$  and  $\Gamma^{k}$ , k = l + 1,...,N is any function of  $z_m$ ,  $l \le m < k$  taking values in  $Y_N$ . A strategy for the second controller is the  $(N-\ell+1)$ -vector  $\Delta = (\Delta^{\ell}, \ldots, \Delta^{N})$  such that  $\Delta^{k}$ ,  $k = \ell, \ldots, N$ , is any function of  $y_m, y_k, \ell \le m < k$  with values in  $Z_N^c$ . For the stochastic game  $(\varepsilon > 0)$  strategies for both players are defined similarly except that the functions  $\Gamma^k, \Delta^k, k = \ell + 1, \ldots, N$ , can depend on  $\eta_m$ ,  $m = \ell, ..., k - 1$  too. A strategy  $\Gamma$  for the deterministic game defines a strategy for the stochastic game in the obvious way. On the other hand, given the random inputs  $\zeta = (\eta_0, \dots, \eta_N)$  a strategy  $\Gamma$  for the stochastic game induces a strategy (denoted by  $\Gamma/\zeta$ ) for the deterministic game. remarks apply to the second controller. Given a pair of strategies  $(\Gamma, \Delta)$ , and a vector of random inputs  $\zeta$  in the stochastic game, the successive moves are found by taking  $y_{\varrho}$  at move 22 - 1 and setting

$$z_{\ell} = \Delta^{\ell}(y_{\ell}), y_{\ell+1} = r^{\ell+1}(y_{\ell}, \eta_{\ell}), \dots$$

Let us indicate explicitly dependence on the strategies  $\Gamma, \Delta$  by writing the payoff in (3.4) as  $\pi^{\epsilon}(s,x,\Gamma,\Delta)$ . Similarly, we write  $\pi(s,x,\Gamma,\Delta)$  in (3.6) when  $\epsilon = 0$ . Note that the game is biased

in favor of the minimizing controller, who knows  $y_k$  before choosing  $z_k$ . The concept of strategy used in [F2] is slightly different, but equivalent to the present one.

Given the initial data (s,x) and N, each of these games has a finite number of possible positions. There are a finite number of control choices for each controller at each move. From the theory of positional games, the stochastic difference game has a value  $W_N^{\varepsilon}(s,x)$  and optimal strategies  $\Gamma^*,\Delta^*$  exist:

$$\pi^{\varepsilon}(s,x,\Gamma,\Delta^{*}) \leq W_{N}^{\varepsilon}(s,x) \leq \pi^{\varepsilon}(s,x,\Gamma^{*},\Delta)$$

for every  $\Gamma, \Delta$ , with equality when  $\Gamma = \Gamma^*, \Delta = \Delta^*$ . In fact,  $W_N(s,x)$  can be defined by backward induction by the functional equation

(3.7) 
$$W_{N}^{\varepsilon}(s,x) = \max_{Y_{N}} \min_{Z_{N}^{c}} E[\delta L(x,y,z) + W_{N}^{\varepsilon}(s+\delta,\psi)], \quad s = t_{\varrho} < T, x \in D,$$

(3.8a) 
$$W_N(s,x) = 0, x \in D$$

$$(3.8b) W_N^{\varepsilon}(T,x) = M\Phi(x),$$

where

$$\psi = x + \delta z + \delta^{1/2} \epsilon^{1/2} \eta$$

and the components  $\eta^{\hat{i}}$  of  $\eta$  are independent random variables, each with values  $\pm 1$  with probability  $\frac{1}{2}$ .

When  $\varepsilon$  = 0 the deterministic difference game has a value  $W_N(s,x)$  satisfying the functional equation corresponding to (3.7) and the conditions (3.8). We shall show that as  $N \to \infty$ ,  $\varepsilon \to 0$ ,  $W_N$  and the function  $I_{MC}^{\varepsilon}$  defined at the end of §2 tend to the same limit. Moreover, this limit  $I_M$  does not depend on c, for large enough c. See Theorem 3.3 and formula (3.15).

We begin with a series of lemmas which give uniform estimates for  $W_N^\epsilon$  -  $W_N$  and for  $W_N^\epsilon(s,x')$  -  $W_N^\epsilon(s,x)$ .

Lemma 3.1. There exist constants  $C_1 = C_1(M)$  and  $N_1$  such that for  $N \ge N_1$  and small  $\varepsilon$ 

$$W_{N}^{\varepsilon}(s,x) \leq C_{1} \operatorname{dist}(x,\partial D) + C_{1}(\delta+n(\delta \varepsilon)^{1/2}), \quad s = t_{\ell}, \quad \ell = 1,...,N, \quad x \in D.$$

<u>Proof.</u> Given  $x_0 \in D$ , let  $x_1$  be a point of  $\partial D$  nearest  $x_0$ . Choose  $x_2$  and  $\Psi(x) = |x-x_2| - |x_1-x_2|$  as in the proof of Lemma 2.4. Let the minimizing controller use the control  $z_k^*$  chosen as follows. Given N, divide  $z^1 = \{|z| \le 1\}$  into nonoverlapping Borel measurable sets  $A_1, \ldots, A_{\nu}$  such that each  $A_i$  contains exactly one point  $z^i \in Z_N^1$  and  $\max_{1 \le i \le \nu} \dim A_i \to 0$  as  $N \to \infty$ . Let  $1 \le i \le \nu$   $2 \le i$  if  $-\Psi_X(x) \in A_i$ . Since  $|\Psi_X| = 1$  there exists  $N_1$  such that

$$\underline{z}(x) \cdot \Psi_{x}(x) \leq -\frac{1}{2}, \quad x \in D, N \geq N_{1}.$$

We take  $z_k^* = \underline{z}(\psi_k)$ ; since we always take  $c \ge 1$ ,  $z_k^* \in Z_N^c$ . In (3.3)

$$\psi_{k+1} = \psi_k + \delta z_k^* + (\delta \epsilon)^{1/2} \eta_k$$

Let the maximizing controller choose  $\textbf{y}_k$  to maximize  $\textbf{L}(\textbf{\psi}_k,\textbf{y},\textbf{z}_k^{\, \star})$  , and let

$$M_k = C_1 \Psi(\psi_k) - W_N(t_k, \psi_k), \text{ if } \psi_k \notin D,$$

where  $C_1$  is chosen below. If  $\psi_k \notin D$  (and hence  $k > F^{\epsilon}$ ) we let

$$M_k = M_F \varepsilon_{+1} = C_1 \Psi (\Psi_F \varepsilon_{+1}).$$

For  $\psi_k \in D$ ,  $k \le N$ , we have by (3.7) and choice of  $y_k$ 

$$W_{N}^{\varepsilon}(t_{k}, \psi_{k}) \leq E[\delta L(\psi_{k}, y_{k}, z_{k}^{*}) + W_{N}^{\varepsilon}(t_{k} + \delta, \psi_{k+1}) | \zeta_{k}]$$

$$\leq \delta L_{1} + E[W_{N}^{\varepsilon}(t_{k} + \delta, \psi_{k+1}) | \zeta_{k}],$$

where  $|L(x,y,\underline{z}(x))| \le L_1$  and  $\zeta_k = (\eta_k,\ldots,\eta_{k-1})$ . By expanding  $\Psi(\Psi_{k+1})$  by Taylor's formula about  $\Psi_k$ ,

$$E[\Psi(\Psi_{k+1}) \mid \varsigma_k] = \Psi(\Psi_k) + \delta z_k^* \cdot \Psi_x(\Psi_k) + O((\delta + (\delta \varepsilon)^{1/2})^2).$$

Since  $\underline{z}(x) \cdot \Psi_X(x) \le -\frac{1}{2}$  for all  $x \in D$ , we have for small  $\varepsilon$  and  $\psi_k \in D$ 

$$E[\Psi(\Psi_{k+1}) | \zeta_{k}] \leq \Psi(\Psi_{k}) - \frac{\delta}{4} ,$$

$$E[M_{k+1} | \zeta_{k}] \leq M_{k} - \frac{\delta C_{1}}{4} + \delta L_{1} \leq M_{k}$$

if  $4L_1 \leq C_1$ . If  $\psi_k \notin D$ , then  $M_{k+1} = M_k$ . Therefore,  $E[M_{k+1} | \zeta_k] \leq M_k$ , which implies by iterating

$$E(M_{N+1}) \leq M_{\lambda}$$
.

Choose  $C_1 \ge 4L_1$  large enough that  $C_1\Psi(x) - M\Phi(x) \ge 0$  on D. If  $F^{\varepsilon} = N$  and  $\Psi_{N+1} \in D$ ,

$$\mathsf{M}_{N+1} \; = \; \mathsf{C}_{1} \Psi \, ( \psi_{N+1} ) \; \; \text{--} \; \; \mathsf{M} \Phi \, ( \psi_{N+1} ) \; \; \text{>--} \; \; 0 \; . \label{eq:Mass_N+1}$$

Otherwise.

$$\mathsf{M}_{\mathsf{N}+1} = \mathsf{C}_1 \Psi (\Psi_{\mathsf{F}^{\varepsilon}+1}) \geq \mathsf{C}_1 [\Psi (\Psi_{\mathsf{F}^{\varepsilon}+1}) - \Psi (\Psi_{\mathsf{F}^{\varepsilon}})]$$

since  $\psi_{F^{\epsilon}} \in D$  and  $\Psi(x) \ge 0$  on D. Since  $|\Psi_{X}| = 1$  we have in the second case

$$M_{N+1} \geq -C_1 |\psi_{F^{\varepsilon_{+1}}} - \psi_{F^{\varepsilon}}| \geq -C_1 (\delta + n(\delta \varepsilon)^{1/2}).$$

Since  $M_{\varrho} = C_1 \Psi(x_0) - W_N^{\varepsilon}(s, x_0)$ ,

$$-C_1(\delta+n(\epsilon\delta)^{1/2}) \leq C_1\Psi(x_0) - W_N^{\epsilon}(s,x_0)$$

Since  $\Psi(x_0) = \text{dist}(x_0, \partial D)$  and  $x_0 \in D$  is arbitrary, this proves Lemma 3.1.

Remark. Similarly, when  $\varepsilon = 0$ , an estimate  $W_N(s,x) \le C_1[\operatorname{dist}(x,\partial D) + \delta]$  holds.

Lemma 3.2. There exists  $C_2$  depending on M and c such that for small  $\epsilon$  and N > N<sub>1</sub>

$$|W_{N}^{\varepsilon}(s,x) - W_{N}(s,x)| \le C_{2}[\varepsilon^{1/2}(T-s)^{1/2} + \delta + (\delta\varepsilon)^{1/2}],$$

$$s = t_{\ell}, \ \ell = 1,...,N, \ x \in D.$$

<u>Proof.</u> Given (s,x) let  $\Gamma$  be an optimal strategy for the maximizing controller in the stochastic game and  $\Delta$  an optimal strategy for the minimizing controller in the deterministic game. Let  $G = \min(F^{\varepsilon}, F)$  with  $F^{\varepsilon}, F$  as in (3.4), (3.6). The strategy  $\Delta$  is played against  $\Gamma$  in the stochastic game, giving by dynamic programming arguments

(\*) 
$$W_{N}^{\varepsilon}(s,x) \leq E\left\{\sum_{k=0}^{G} \delta L(\psi_{k},y_{k},z_{k}) + W_{N}^{\varepsilon}(t_{G+1},\psi_{G+1})\right\}.$$

Given a vector  $\zeta = (\eta_{\ell}, \ldots, \eta_{N})$  of random inputs to (3.3), the strategy  $\Gamma/\zeta$  is played against  $\Delta$  in the deterministic game. We have

(\*\*) 
$$W_N(s,x) \ge \sum_{k=l}^{G} \delta L(\phi_k, y_k, z_k) + W_N(t_{G+1}, \phi_{G+1}),$$

for each  $\zeta$ . Hence, the same inequality holds if we take the expectation of the right side.

By 
$$(3.3)$$
,  $(3.5)$ 

$$\psi_{k+1} - \phi_{k+1} = \varepsilon^{1/2} w_k$$

where

$$w_k = \delta^{1/2} \sum_{m=0}^{k} n_m.$$

By (2.1),  $L(\cdot,y,z)$  is Lipschitz with some constant  $K_1$ , for  $|z| \le c$ . Moreover,  $\phi$  is Lipschitz with some constant  $K_2$ .

Let 
$$||w|| = \max\{|w_k|: k = \ell, ..., N+1\}$$
. Then 
$$\sum_{k=\ell}^{G} \delta |L(\psi_k, y_k, z_k) - L(\phi_k, y_k, z_k)| \le K_1(T-s) \varepsilon^{1/2} ||w||,$$
 
$$|M\Phi(\psi_{N+1}) - M\Phi(\phi_{N+1})| \le MK_2 \varepsilon^{1/2} ||w||.$$

We subtract the expectation of (\*\*) from (\*), and recall that  $W_N(t_{G+1},\phi_{G+1}) \ge 0 \quad \text{together with (3.8):}$ 

$$W_N^{\epsilon}(s,x) - W_N(s,x) \le (K_1(T-s) + MK_2)\epsilon^{1/2}E||w||$$
  
+  $E\{W_N^{\epsilon}(t_{G+1},\psi_{G+1}); G < N, \psi_{G+1} \in D\}.$ 

Now G < N,  $\psi_{G+1} \in D$  imply  $\phi_{G+1} \notin D$ , and

$$dist(\psi_{G+1}, \partial D) \leq |\psi_{G+1} - \phi_{G+1}| \leq \varepsilon^{1/2} ||w||.$$

By Lemma 3.1 we have

$$\begin{split} & E\{W_N^{\varepsilon}(t_{G+1}, \psi_{G+1}); \ G < N, \ \psi_{G+1} \in D\} \\ & \leq C_1(\varepsilon^{1/2} E||w|| + \delta + n(\delta \varepsilon)^{1/2}). \end{split}$$

Since the sequence of components  $w_k^i$ , i = 1,...,n, form a martingale with  $w_{\ell-1}^i = 0$  we have [D, p. 311]

(3.9) 
$$E||w|| \le 2nE|w_N^i| \le 2n(E|w_N^i|^2)^{1/2} = 2n(T-s)^{1/2}$$
.

Therefore, for some constant C2

$$W_N^{\varepsilon}(s,x) - W_N(s,x) \leq C_2 \varepsilon^{1/2} (T-s) + C_2 (\delta + (\delta \varepsilon)^{1/2}).$$

The opposite inequality is proved in the same way, by taking  $\Gamma$  optimal for the deterministic game and  $\Delta$  optimal for the stochastic game, and using the Remark after Lemma 3.1.

Lemma 3.3. There exists a constant R depending on M, such that for small  $\epsilon$  and  $N \geq N_1$ 

$$|W_N^{\varepsilon}(s,x) - W_N^{\varepsilon}(s,x')| \le R|x-x'| + R(\delta + (\delta\varepsilon)^{1/2}),$$

$$s = t_{\ell}$$
,  $\ell = 1, ..., N$ ,  $x$ ,  $x' \in D$ .

<u>Proof.</u> Let  $\Gamma$  be an optimal strategy for the maximizing controller, for initial data (s,x); and let  $\Delta$  be an optimal strategy for the minimizing controller, for initial data (s,x'), in the stochastic game. We use the strategies  $\Gamma,\Delta$  both in the game with initial data (s,x) and in the game with initial data (s,x'). Let  $\psi_k,\psi_k'$  be the solutions to (3.3) with  $\psi_\ell(s)=x$ ,  $\psi_\ell'(s)=x'$ . [Recall that strategies are expressed in terms of past control choices and random inputs, but not in terms of the states  $\psi_k$ .] Let  $G=\min(F^\epsilon,F^{\epsilon'})$  where  $F^\epsilon,F^{\epsilon'}$  are the corresponding stopping times in (3.4). Then

$$w_{N}^{\varepsilon}(s,x) \leq E\{\sum_{k=\ell}^{G} \delta L(\psi_{k},y_{k},z_{k}) + w_{N}^{\varepsilon}(t_{G+1},\psi_{G+1})\},$$

$$w_{N}^{\varepsilon}(s,x') \geq E\{\sum_{k=\ell}^{G} \delta L(\psi_{k},y_{k},z_{k}) + w_{N}^{\varepsilon}(t_{G+1},\psi_{G+1})\}.$$

By (3.3),  $\psi_k - \psi_k' = x - x'$ . We then have as in the proof of Lemma 3.2

$$(*) \quad W_{N}^{\varepsilon}(s,x) - W_{N}^{\varepsilon}(s,x') \leq E \sum_{k=\ell}^{G} \delta |L(\psi_{k},y_{k},z_{k}) - L(\psi_{k}',y_{k},z_{k})|$$

$$+ MK_{2}|x-x'| + E\{W_{N}^{\varepsilon}(t_{G+1},\psi_{G+1}); G < N, \psi_{G+1} \in D\}.$$

The terms on the right side of (\*) are estimated as follows. By (2.1) and (2.2), for some  $\Lambda_1$ 

$$|L(\psi_k, y_k, z_k) - L(\psi_k, y_k, z_k)| \le \Lambda_1(1 + L(\psi_k, y_k, z_k))|x - x'|.$$

Since  $\Delta$  is optimal for initial data (s,x'),

$$E \sum_{k=\ell}^{G} \delta L(\psi_{k}', y_{k}, z_{k}) \leq W_{N}^{\epsilon}(s, x').$$

If G < N,  $\psi_{G+1} \in D$ , then  $\psi'_{G+1} \notin D$  and

$$dist(\psi_{G+1}, \partial D) \leq |\psi_{G+1} - \psi'_{G+1}| = |x-x'|.$$

On the right side of (\*), we have:

1st term 
$$\leq \Lambda_1 (T-s+W_N^{\epsilon}(s,x'))|x-x'|$$
.

By Lemma 3.1

3rd term 
$$\leq C_1|x'-x| + C_1(\delta + n(\delta \epsilon)^{1/2}).$$

Since dist(x,  $\partial D$ )  $\leq$  diam  $D < \infty$ , another application of Lemma 3.1 gives a bound on  $W_N^{\epsilon}(s,x')$ . Hence, for some constant R

$$W_N^{\varepsilon}(s,x) - W_N^{\varepsilon}(s,x') \leq R|x-x'| + R(\delta + (\delta \varepsilon)^{1/2}).$$

Since the roles of x and x' can be exchanged, this proves Lemma 3.3.

We will next show that, for fixed  $\varepsilon$ ,  $W_N^\varepsilon(s,x)$  tends to  $I_{MC}^\varepsilon$  as  $N \to \infty$ . The main step in doing this is Lemma 3.5. To make the backward induction in that Lemma, we use the following slightly different payoff for the discrete-time stochastic difference game. Let  $D_\rho$  be the  $\rho$ -neighborhood of D. Let  $J^\varepsilon$  be an extension of  $I_{MC}^\varepsilon$  to a cylinder  $[0,T] \times D_\rho$ , for some  $\rho > 0$ , as follows:

$$J^{\varepsilon}(s,x) = I^{\varepsilon}_{Mc}(s,x), \quad \text{if} \quad x \in \overline{\mathbb{D}},$$
 
$$J^{\varepsilon}(s,x_1+rz(x_1)) = J^{\varepsilon}(s,x_1-rz(x_1)) + 2rJ^{\varepsilon}_{v}(s,x_1)$$

for  $x_1 \in \partial D$ ,  $z(x_1)$  the exterior unit normal to D at  $x_1, J_{\nu}^{\varepsilon}$ 

the normal derivative,  $0 < r < \rho$ . The function  $J^{\epsilon}$  belongs to  $C^{0,1}_{\beta}([0,T] \times \overline{D}_{\rho})$  and to  $C^{1,2}_{\beta}([0,T'] \times \overline{D}_{\rho})$  for any T' < T and  $\beta \in (0,1)$ . Moreover, if  $\operatorname{dist}(x,\partial D) < \rho$ ,

$$|J^{\varepsilon}(s,x)| \leq S\rho$$

where S = 3B with B = B(M) as in Lemma 2.4. Instead of (3.4) we take the payoff

$$\tilde{\pi}^{\varepsilon}(s,x) = E\{\sum_{k=\ell}^{F^{\varepsilon}} \delta L(\psi_k, y_k, z_k) + J^{\varepsilon}(t_{F^{\varepsilon}+1}, \psi_{F^{\varepsilon}+1})\}.$$

Let  $\widetilde{W}_N^{\varepsilon}(s,x)$  denote the value of the stochastic difference game with payoff  $\widetilde{\pi}^{\varepsilon}(s,x)$ ,  $x \in D$ . For  $x \in D_{\rho}$  - D let  $\widetilde{W}_N^{\varepsilon}(s,x) = J^{\varepsilon}(s,x)$ . If  $F^{\varepsilon} = N$  and  $\psi_{N+1} \in D$ , the last term is  $M \Phi(\psi_{N+1})$  as in (3.4). Otherwise,  $\psi_F \in D$ ,  $\psi_{F^{\varepsilon+1}} \notin D$ . By (3.3) and the fact that  $|\eta_k^i| = 1$ ,  $|z_k| \le c$ ,

$$dist(\psi_{F^{\epsilon_{+1}}}, \partial D) \leq |\psi_{F^{\epsilon_{+1}}} - \psi_{F^{\epsilon}}| < \rho$$

provided N  $_{2}$  N $_{1}$  where N $_{1}$  is large enough that

(3.12) 
$$c\delta + n\epsilon^{1/2}\delta^{1/2} < \rho$$

By (2.12)  $\phi(\psi_{F^{\epsilon}+1}) = 0$  if  $\psi_{F^{\epsilon}+1} \notin D$ . By (3.11) we have for  $N \ge N_1$ ,  $|\tilde{\pi}^{\epsilon} - \pi^{\epsilon}| \le S\rho$  for every pair of strategies  $\Gamma, \Delta$ . Hence

(3.13) 
$$|\widetilde{W}_{N}^{\varepsilon}(s,x) - W_{N}^{\varepsilon}(s,x)| \leq S\rho,$$

for all  $s = t_{\ell}$ ,  $\ell = 1,...,N$ ,  $x \in D$ . For fixed  $\epsilon$  and N let

(3.14) 
$$q_{\ell} = \sup_{x \in D} |\widetilde{W}_{N}^{\varepsilon}(t_{\ell}, x) - J^{\varepsilon}(t_{\ell}, x)|.$$

By choice of  $\tilde{\pi}^{\varepsilon}$ ,  $q_{N+1}=0$ . In Lemmas 3.4 and 3.5, M,c, $\varepsilon$  are fixed. The constants appearing in those lemmas may depend on M,c, $\varepsilon$ .

Lemma 3.4. There exist S<sub>1</sub>, N<sub>2</sub> such that

$$|\tilde{W}_{N}^{\varepsilon}(s,x) - \Phi(x)| \leq S_{1}(T-s)^{1/2} + S_{1}\rho$$

for  $N \ge N_2$ ,  $0 < T - s \le 1$ ,  $x \in D$ .

<u>Proof.</u> Consider any pair of strategies  $\Gamma, \Delta$  for a stochastic game with initial data  $s = t_{\ell}$ ,  $x = \psi_{\ell}$ . We have, for some B,  $0 \le L \le B$  on  $Q \times Y \times Z^{C}$ . Choose  $N_{2}$  such that (3.12) holds for  $N \ge N_{2}$ . Then

$$|\tilde{\pi}^{\varepsilon}(s,x) - \phi(x)| \leq B(T-s) + ME|\phi(\psi_{F^{\varepsilon}+1}) - \phi(x)|$$

$$+ E|J^{\varepsilon}(t_{F^{\varepsilon}+1}, \psi_{F^{\varepsilon}+1}) - M\phi(\psi_{F^{\varepsilon}+1})|$$

The last term is 0 if  $F^{\varepsilon} = N$ ,  $\psi_{N+1} \in D$ ; otherwise  $\Phi(\psi_{F^{\varepsilon}+1}) = 0$ 

and dist( $\psi$ ,  $\partial D$ ) <  $\rho$  by (3.12). By (3.3), (3.9) and the fact that  $|z_k| \le c$ ,

$$E|\psi_{F^{\varepsilon_{+1}}} - x| \le c(T-s) + 2n\varepsilon^{1/2}(T-s)^{1/2}$$
.

Let K be a Lipschitz constant for  $\phi$ . Then, for  $0 < T - s \le 1$ ,

$$|\tilde{\pi}^{\varepsilon}(s,x) - \Phi(x)| \leq B(T-s) + MK(c+2n\varepsilon^{1/2})(T-s) + S\rho$$

with S as in (3.11). We take

$$S_1 = \max[B+MK(c+np\epsilon^{1/2}), S].$$

Since the above inequality holds for any  $\Gamma,\Delta$  we get Lemma 3.4.

Since  $J^{\varepsilon}$  is Hölder continuous on  $\overline{Q}$ ,  $|J^{\varepsilon}(s,\cdot) - J^{\varepsilon}(T,\cdot)|$  is uniformly small on D if T - s is small. Since  $J^{\varepsilon}(T,x) = \Phi(x)$  for  $x \in D$ , from Lemma 3.4 we have the:

Corollary. Given a > 0 there exist k > 0 and  $N_2$  such that  $q_{\ell} < a$  if 0 < T - s < k,  $s = t_{\ell}$ ,  $N \ge N_2$ .

Lemma 3.5. Given T' < T there exist constants A > 0,  $0 < \alpha < \frac{1}{2}$  such that the following is true: given  $\mu > 0$  there exists  $N_0$  such that for  $N \ge N_0$ 

$$q_{\ell} \leq (\mu + A \delta^{\alpha}) (T' - s) + q_{m}$$

for  $s = t_{\ell} \le t_{m} \le T'$ .

<u>Proof.</u> The function  $J^{\varepsilon}$  is of class  $C_{\beta}^{1,2}([0,T']\times\overline{\mathbb{D}}_{\rho})$  for any  $\beta\in(0,1)$ . Let  $\alpha=\beta/2$ . As above we take  $N\geq N_2$  large enough that, for any  $x\in D$ ,  $|z|\leq c$ ,  $\eta=(\eta^1,\ldots,\eta^n)$  with  $\eta^1=\pm 1$ ,

$$\psi = x + \delta z + \delta^{1/2} \epsilon^{1/2} \eta$$

belongs to  $D_{\rho}$ . By Taylor's formula

$$\begin{split} J^{\varepsilon}(s+\delta,\psi) &= J^{\varepsilon}(s,\psi) + \delta J^{\varepsilon}_{s}(s,\psi) + \bigoplus_{1}, \\ \\ J^{\varepsilon}(s,\psi) &= J^{\varepsilon}(s,x) + J^{\varepsilon}_{x}(s,x) \cdot (\psi - x) \\ &+ \frac{1}{2} \sum_{i,j=1}^{n} J^{\varepsilon}_{x_{i}x_{j}}(s,x) \cdot (\psi^{i} - x^{i}) \cdot (\psi^{j} - x^{j}) + \bigoplus_{2}, \end{split}$$

where for suitable constants  $A_1, A_2$ 

$$|\bigoplus_{1}| \leq A_{1}\delta^{1+\alpha}$$
,  $|\bigoplus_{2}| \leq A_{2}|\psi-x|^{2+2\alpha}$ ,  $\beta = 2\alpha$ .

Since

$$|J_{s}^{\varepsilon}(s,\psi) - J_{s}^{\varepsilon}(s,x)| \leq A_{3}|\psi - x|^{2\alpha}$$

we have

$$J^{\varepsilon}(s+\delta,\psi) = J^{\varepsilon}(s,x) + \delta J^{\varepsilon}_{s}(s,x) + J^{\varepsilon}_{x}(s,x) \cdot (\psi-x)$$

$$+ \frac{1}{2} \int_{i,j=1}^{n} J^{\varepsilon}_{x_{i}x_{j}}(s,x) (\psi^{i}-x^{i}) (\psi^{j}-x^{j}) + \underbrace{\mathbb{H}}_{3},$$

where

$$|H|_{3}| \leq A_{4}(\delta^{1+\alpha}+\delta|\psi-x|^{2\alpha}+|\psi-x|^{2+2\alpha}).$$

By taking expectations, we have

$$\begin{split} \mathrm{EJ}^{\varepsilon}(s+\delta,\psi) &= \mathrm{J}^{\varepsilon}(s,x) + \delta[\mathrm{J}_{s}^{\varepsilon}(s,x) + \mathrm{J}_{x}^{\varepsilon}(s,x) \cdot z \\ &+ \frac{\varepsilon}{2} \Delta_{x} \mathrm{J}^{\varepsilon}] + \mathrm{H}, \\ \mathrm{H} &= \mathrm{E}\mathrm{H}_{3} + \frac{\delta^{2}}{2} \sum_{i,j=1}^{n} z^{i} z^{j} \mathrm{J}_{x_{i}}^{\varepsilon} x_{j}. \end{split}$$

Now L is uniformly continuous on  $\overline{\mathbb{D}} \times Y \times Z^{C}$  and  $J_{X}^{\varepsilon}$  is uniformly continuous on  $\overline{\mathbb{Q}}$ . By (2.22), given  $\mu > 0$  there exist  $N_0 \geq N_1$  and a function  $y^*$  from  $\overline{\mathbb{Q}}$  into the finite set  $Y_{N_0}$ , such that

$$L(x,\underline{y}^*(s,x),z) + J_x^{\varepsilon}(s,x) \cdot z \geq H^{c}(x,J_x^{\varepsilon}(s,x)) - \mu$$

for all  $(s,x) \in \overline{\mathbb{Q}}$ ,  $|z| \le c$ .

If  $\gamma < 3$ 

$$|\psi - x|^{\gamma} = |\delta z| + \varepsilon^{\frac{1}{2} \delta^{\frac{1}{2}} \eta} |^{\gamma} \leq A_5 (\delta^{\gamma} + (\varepsilon^{\frac{1}{2} \delta^{\frac{1}{2}} |\eta|)^{\gamma}})$$

and  $E|\eta^i|^{\gamma} = 1$ , i = 1,...,n. We have

$$E|H_3| \le A_6[\delta^{1+\alpha} + \delta^{1+2\alpha} + \delta^{2+2\alpha}].$$

For  $N_0$  large enough,  $\delta < 1$  and

$$|H| \leq A\delta^{1+\alpha}$$

for suitable A.

Since  $J^{\varepsilon} = I_{Mc}^{\varepsilon}$  is a solution of (2.21) in Q, we have for  $x \in D$ ,  $y^* = y^*(s,x)$ 

$$E\{\delta L(x,\underline{y}^*,z) + J^{\varepsilon}(s+\delta,\psi)\} \geq J^{\varepsilon}(s,x) - \delta\mu - A\delta^{1+\alpha}.$$

Let us now estimate  $q_{\ell}$  in terms of  $q_{\ell+1}$ . By (3.14)

$$J^{\varepsilon}(s+\delta,\psi) \leq q_{\ell+1} + \tilde{W}^{\varepsilon}_{N}(s+\delta,\psi)$$

if  $\psi \in D$ . This inequality holds also for  $\psi \notin D$ , since  $J^{\varepsilon} = \widetilde{w}_{N}^{\varepsilon}$  by definition in that case. Hence, for all  $z \in Z^{C}$ 

$$E\{\delta L(x,y^*,z) + \widetilde{W}_N^{\varepsilon}(s+\delta,\psi)\} \geq J^{\varepsilon}(s,x) - \delta \mu - A\delta^{1+\alpha} - q_{\ell+1}.$$

Since  $\tilde{\mathbf{w}}_{N}^{\epsilon}$  satisfies the functional equation (3.7), this implies

$$\widetilde{W}_{N}^{\varepsilon}(s,x) \geq J^{\varepsilon}(s,x) - \delta\mu - A\delta^{1+\alpha} - q_{\ell+1}$$

A similar argument, choosing  $\underline{z}^* = \underline{z}^*(s,x,y)$  with values in  $Z_{N_0}^c$  such that

$$L(x,y,\underline{z}^*) + J_X^{\varepsilon} \cdot \underline{z}^* \leq H^{c}(x,J_X^{\varepsilon}(s,x)) + \mu$$

for all  $(s,x) \in \overline{Q}$ ,  $y \in Y$ , shows that

$$\widetilde{W}_{N}^{\varepsilon}(s,x) \leq J^{\varepsilon}(s,x) + \delta\mu + A\delta^{1+\alpha} + q_{\ell+1}.$$

Therefore,

$$q_{\ell} \leq \delta(\mu + A\delta^{\alpha}) + q_{\ell+1}$$

Since  $\delta(m-\ell) = t_m - t_\ell \le T' - s$ , this proves Lemma 3.5.

By (3.12) the number  $\rho$  in (3.13) can be chosen arbitrarily small if N is large enough. By (3.13), Lemma 3.5, and the Corollary to Lemma 3.4 we have:

Theorem 3.1. For fixed  $\varepsilon, \widetilde{W}_{N}^{\varepsilon}(s,x) - I_{MC}(s,x)$  and  $W_{N}^{\varepsilon}(s,x) - I_{MC}(s,x)$  tend to 0 as  $N \to \infty$ , uniformly for  $x \in D$ ,  $s = t_{\ell}$ ,  $\ell = 1, \ldots, N$ .

As in [F2] we call  $I_{MC}^{\varepsilon}$  the <u>lower value</u> of the penalized stochastic differential game, for initial data  $(s,x) \in Q$ . From Lemma 3.3 and Theorem 3.1 we have the following uniform Lipschitz condition for  $I_{MC}^{\varepsilon}(s,\cdot)$ .

Theorem 3.2. There exists a constant R = R(M), such that for small  $\epsilon$ 

$$|I_{MC}^{\varepsilon}(s,x) - I_{MC}^{\varepsilon}(s,x')| \le R|x-x'|$$
,  $x,x' \in D$ ,  $0 \le s \le T$ .

Theorem 3.2 implies the a priori estimate on the gradient  $|(I_{MC})_x| \le R$ .

By (1.8) the minimum over  $z \in E^n$  of  $L + p \cdot z$  is attained at z = b + p. Since  $|b(x,y)| \le B_1$ ,  $|p| \le R$  implies  $|b+p| \le B_1 + R$ . Hence, by (2.11), (2.22)

$$H^{C}(x,p) = H(x,p), |p| \le R, c \ge E_1 + R.$$

Let 
$$p = (I_{MC}^{\varepsilon})_{x}$$
,  $c(M) = B_{1} + R(M)$ . By (2.7), (2.9<sub>M</sub>) and (2.21)

$$(3.15) I_{MC}^{\varepsilon} = I_{M}^{\varepsilon}, c \ge c(M).$$

Let us now take s=0. Since b=b(x,y) the problem is autonomous, and hence this is no real restriction (see, in particular (2.16)). Lemma 3.2 gives a uniform estimate for  $W_N^{\varepsilon} - W_N$ , which tends to 0 as  $N \to \infty$ ,  $\varepsilon \to 0$ . Since  $J^{\varepsilon} = I_{MC}^{\varepsilon}$  on Q for  $c \ge c(M)$ , we have

Theorem 3.3. As  $\varepsilon \to 0$ ,  $I_M^{\varepsilon}(0,x)$  tends to a limit  $I_M(0,x)$ .

Moreover,  $W_N(0,x) \to I_M(0,x)$  tends to 0 as  $N \to \infty$ , uniformly for  $x \in D$ .

As in [F2] we call  $I_M(0,x)$  the <u>lower value</u> of the deterministic penalized game starting at  $x \in D$ . As in §2 let us also denote this lower value by  $I_M(0,x;T)$  to indicate dependence on the final time T. By (2.15),  $I_M$  is nondecreasing in M, and by Lemma 2.1,  $I_M$  is bounded above for fixed T > 0. Hence,

 $I_{M}(0,x;T)$  is nondecreasing in M and bounded above. Let

(3.16) 
$$I(0,x;T) = \lim_{M\to\infty} I_M(0,x;T), \quad x \in D.$$

4. Main Results. In this section, we show that  $I^{\varepsilon} = -\varepsilon \log q^{\varepsilon}$  tends to a limit I as  $\varepsilon \to 0$ , and interpret I as the lower value of the differential game described formally in §1. In view of (2.16) it suffices to consider initial time s = 0, as already noted at the end of §3. The discrete time games in §3 then start with  $\ell = 1$ . We recall that the value  $W_N(0,x)$  of the deterministic penalized game in §3 depends also on M and C. For T' < T, let  $a = T'T^{-1}$ . In the following lemma,  $W_N'(0,x)$  denotes the value of the corresponding game in which T is replaced by T' and C by  $a^{-1}C$ .

Lemma 4.1. Let  $\frac{1}{2}$  T < T' < T. There exist constants  $R_1, N_1, c^*$  (depending on T) such that  $|W_N(0,x) - W_N'(0,x)| \le R_1(T-T')$  for any  $M, N \ge N_1, c \ge c^*$ .

<u>Proof.</u> Let  $\delta = TN^{-1}$ ,  $\delta' = a\delta = T'N^{-1}$ . For any pair of strategies  $(\Gamma, \Delta)$  for the discrete time deterministic game in 3 with time-step  $\delta$ , we consider the corresponding strategies  $(\Gamma', \Delta')$  for a game with time-step  $\delta'$ , in such a way that

$$\phi_1^! = \phi_1^! = x, y_k^! = y_k^!, z_k^! = a^{-1}z_k^!, k = 1,...,N,$$

where  $\phi_k^i$  denotes the state and  $y_k^i, z_k^i$  the controls for the latter game. By (3.5) we have  $\phi_k^i = \phi_k$  for all k. We wish to

estimate the difference of the respective payoffs  $\pi, \pi'$ . By (1.8), (3.6)

$$\pi - \pi' = \frac{1}{2} \sum_{k=1}^{F} \delta[(1-a)|b_k|^2 + (1-a^{-1})|z_k|^2]$$

where  $b_k = b(\phi_k, y_k)$ . Since 0 < a < 1, the first term in the sum is positive, and the second term is negative. Since  $|b_k| \le B_1$ ,

$$\pi < \pi' + \frac{1}{2} B_1 T (1-a)$$
.

Since this is true for any  $\Gamma, \Delta$ , and since Ta = T',

(\*) 
$$W_N(0,x) \leq W_N'(0,x) + \frac{1}{2} B_1(T-T')$$
.

On the other hand, from (2.2), (3.6), and  $\phi \ge 0$ 

$$\pi' \leq \pi + \frac{a^{-1}-1}{2} \sum_{k=1}^{F} \delta |z_k|^2 \leq \pi + \frac{a^{-1}-1}{2c_1} (\pi + c_2 T),$$

$$W_N'(0,x) \leq W_N(0,x) + \frac{T-T'}{2c_1 T'} (W_N(0,x) + c_2 T).$$

Let us show that  $W_N(0,x) \leq K$  for  $N_-N_1$ ,  $c \geq c^*$  where K,  $N_1$  and  $c^*$  depend only on T. For this purpose, consider any  $z_0 \in Z_N^1$  with  $|z_0| \geq 1/2$ . Let the minimizing controller use the constant control  $z_k = c^*z_0$ , where  $\frac{1}{2}c^*T > \text{diam D.}$  With this choice, there exists  $N_1$  such that exit occurs by step F < N for  $N \geq N_1$ . Moreover, the payoff  $\pi$  satisfies  $\pi \leq \delta FL^* \leq TL^*$  where  $L^*$  is a bound for L(x,y,z)

when  $|z| \le c^*$ . Let  $K = TL^*$ . Since T' < T < 2T'

(\*\*) 
$$W_N'(0,x) \leq W_N(0,x) + \frac{(L^*+c_2)}{c_1} (T-T')$$

By (\*) and (\*\*),  $|W_N'(0,x) - W_N(0,x)| \le R_1(T-T')$  where  $R_1$  does not depend on M. This proves Lemma 4.1.

We have by Lemma 4.1, Theorem 3.3, and (3.16):

Corollary 4.1. 
$$|I_{M}(0,x;T') - I(0,x;T)| \le R_{1}(T-T')$$
  
 $|I(0,x;T') - I(0,x;T)| \le R_{1}(T-T').$ 

By combining results above we obtain the first main theorem.

Theorem 4.1.  $I(0,x;T) = \lim_{\varepsilon \to 0} I^{\varepsilon}(0,x;T)$  for every  $x \in D$  and T > 0.

 $\underline{\text{Proof.}}$  Consider T' < T. By Lemma 2.3 and Theorem 3.3, for large enough M

$$\lim_{\varepsilon \to 0} \sup_{\varepsilon \to 0} I^{\varepsilon}(0,x;T) \leq I_{M}(0,x;T').$$

Since  $I_{M}^{\varepsilon} \leq I^{\varepsilon}$ , for each M

$$\lim_{\varepsilon \to 0} \inf I^{\varepsilon}(0,x;T) \ge \lim_{\varepsilon \to 0} I^{\varepsilon}_{M}(0,x;T) = I_{M}(0,x;T).$$

Hence by (3.16) and Corollary 4.1

$$\lim_{\varepsilon \to 0} \sup_{T} I^{\varepsilon}(0,x;T) \leq I(0,x;T) + R_{1}(T-T')$$

$$\lim_{\varepsilon \to 0} \inf I^{\varepsilon}(0,x;T) \geq I(0,x;T).$$

Since T - T' can be made arbitrarily small, this proves Theorem 4.1.

It remains to characterize I as a lower value. Let us discretize time as in §3, and define a deterministic game as follows. The dynamics are again (3.5), and strategies  $\Gamma, \Delta$  are as in §3. However, instead of (3.6) the payoff is now

(4.1) 
$$\pi_{\infty}(0,x;\Gamma,\Delta) = \sum_{k=1}^{F} \delta L(\phi_k,y_k,z_k) + \chi$$

where  $\chi$  = + $\infty$  if F = N and  $\varphi_{N+1}$   $\in$  D and  $\chi$  = 0 otherwise. Let

$$(4.2) \qquad V_{N}^{C}(0,x;T) = \inf_{|\Delta| < c} \sup_{\Gamma} \pi_{\infty}(0,x;\Gamma,\Delta).$$

The notation  $|\Delta| \le c$  means  $|\Delta^k| \le c$  for each k; this is the same bound imposed in §3. We now write  $W_N(0,x;T)$  for the value  $W_N(0,x)$  for the penalized deterministic game in §3; recall that  $W_N$  depends also on M and c.

Lemma 4.2. Let  $0 < \beta < \frac{1}{2}$ . There exist  $c^*, M_1, N_1$  (depending on T and  $\beta$ ) and a constant  $L_1$  such that

$$W_N(0,x;T) \leq V_N^c(0,x;T) \leq W_{\widehat{N}}(0,x;\widehat{T}) + L_1(T-\widehat{T})$$

for all  $M \ge M_1$ ,  $\hat{T} = \hat{N}\delta$ ,  $N_1 \le \hat{N} < N$ ,  $T - \hat{T} \ge \beta T$ ,  $c \ge c_1^*$ .

Proof. The payoff  $\pi(=\pi_M)$  in (3.6) satisfies  $\pi \leq \pi_\infty$ . Hence, we have the left-hand inequality in Lemma 4.2. To obtain the right-hand inequality, let the maximizing controller choose any strategy  $\Gamma$ . We define a strategy  $\Delta$  for the minimizing controller as follows. Let  $\hat{\Delta}$  be an optimal strategy for the penalized game with  $\hat{N}$  moves. The strategy  $\Delta$  agrees with  $\hat{\Delta}$  on moves 2k,  $k=1,\ldots,\hat{N}$ . Let  $\hat{F}$  be the first step when  $\hat{F}+1$   $\hat{F}+$ 

$$\sum_{k=1}^{\hat{N}} \delta L(\phi_k, y_k, z_k) + M \Phi(\phi_{\hat{N}+1}) \leq W_{\hat{N}}(0, x; \hat{T})$$

since  $\hat{\Delta}$  is optimal. Let  $c_1^* = 4T^{-1} \text{diam D.}$  For  $c \ge c_1^*$ , the right side is bounded, as shown in the proof of Lemma 4.1. By (2.12) and the fact that  $L \ge 0$ ,

$$dist(\phi_{\hat{N}+1}, \partial D) \leq CM^{-1}$$

for some C. Let A be the  $\alpha$ -neighborhood of  $\partial D$ , for suitable  $\alpha < \beta T$ . We choose  $\alpha$  small enough that, for every  $x \in A$ , there exists  $\underline{z}(x) \in Z_N^2$  such that  $x + s\underline{z}(x) \notin D$  for some s > 0,  $s < \alpha$ . Let  $M_1 \geq C\alpha^{-1}$ . When  $\hat{F} = \hat{N}$  and  $\hat{\phi} \in D$ , then  $\hat{\phi} \in A$  for  $M \geq M_1$ . In this case, let  $z_k = \underline{z}(\hat{\phi})$  for  $k = \hat{N} + 1, \ldots, N$ . For N large, the first F when  $\hat{\phi}_{F+1} \notin D$  satisfies F < N since  $T - \hat{T} \geq \beta T > \alpha$ .

If  $\phi_{\hat{F}+1} \notin D$ , then  $\hat{F} = F$ . Otherwise,

$$\delta(F-\hat{F}) \leq \delta(N-\hat{N}) = T - \hat{T}.$$

When  $|z| \le 2$ ,  $L(x,y,z) | \le L_1$  for some  $L_1$ . Then

$$\pi_{\infty} = \sum_{k=1}^{\hat{F}} L(\phi_{k}, y_{k}, z_{k}) + \sum_{k=\hat{F}+1}^{F} L(\phi_{k}, y_{k}, \underline{z}(\phi_{\hat{N}+1}))$$

$$\leq W_{\hat{N}}(0, x; \hat{T}) + L_{1}(T-\hat{T}).$$

For this strategy  $\Delta$ ,

$$\sup_{\Gamma} \pi_{\infty}(0,x;\Gamma,\Delta) \leq W_{\widehat{N}}(0,x;\widehat{T}) + L_{1}(T-\widehat{T}),$$

which gives Lemma 4.2.

The function  $V_N^C$  in (4.2) is clearly a nonincreasing function of c. Let  $V_N = \lim_{C \to \infty} V_N^C$ . Then

$$(4.3) V_{N}(0,x;T) = \inf_{\Delta} \sup_{\Gamma} \pi_{\infty}(0,x;\Gamma,\Delta)$$

where the strategy  $\Delta$  for the minimizing controller is now chosen without the constraint  $|\Delta| \le c$ . Let  $y^N = (y_1, y_2, \ldots, y_N)$  denote any sequence of control choices for the maximizing controller,  $y_k \in Y_N$ . Thus  $y^N$  is an open loop strategy. Then

$$V_{N}^{C}(0,x;T) = \inf_{\substack{|\Delta| \leq c \ y^{N}}} \sup_{x \in \mathbb{R}^{N}} (0,x;y^{N},\Delta)$$

$$V_{N}(0,x;T) = \inf_{\Delta} \sup_{y^{N}} (0,x;y^{N},\Delta).$$

To see this, clearly  $\geq$  holds in (4.4). On the other hand, any pair of strategies  $\Gamma, \Delta$  and initial state x define sequences y,z with  $\Gamma^1 = y_1$  and

$$z_1 = \Delta^1(y_1), y_2 = \Gamma^2(z_1), z_2 = \Delta^2(y_1, y_2), \dots$$

and  $\pi_{\infty}(0,x;y^N,\Delta) = \pi_{\infty}(0,x;\Gamma,\Delta)$ .

We use the following truncation procedure. Let  $\pi_N \colon Z_N \to Z_N^C$  be such that  $\pi_N(z) = z$  if  $z \in Z_N^C$  (recall that  $Z_N^C = Z_N \cap \{|z| \le c\}$ . Given a sequence  $z^N = (z_1, \ldots, z_N)$ , let  $\tilde{z}_k = \pi_N(z_k)$ . Given a strategy  $\Delta = (\Delta^1, \ldots, \Delta^N)$  let  $\tilde{\Delta} = (\tilde{\Delta}^1, \ldots, \tilde{\Delta}^N)$  where  $\tilde{\Delta}^k = \pi_N \circ \Delta^k$ . As in (3.5) define  $\phi_k, \tilde{\phi}_k$  by

$$\phi_{k+1} = \phi_k + \delta_{z_k}, \quad \tilde{\phi}_{k+1} = \tilde{\phi}_k + \delta_{z_k}, \quad \phi_1 = \tilde{\phi}_1 = x.$$

For  $1 \le F \le N$ , we use the notation

$$||\phi||_F = \max_{1 \le k \le F+1} |\phi_k|.$$

Lemma 4.3. Given K > 0 there exists B = B(K) such that  $\sum_{k=1}^{F} \delta |z_k|^2 \le K \text{ implies } ||\phi - \tilde{\phi}||_F \le 2Kc^{-1} \text{ and }$ 

$$\sum_{k=1}^{F} \delta L(\tilde{\phi}_k, y_k, \tilde{z}_k) \leq \sum_{k=1}^{F} \delta L(\phi_k, y_k, z_k) + Bc^{-1}.$$

<u>Proof.</u> Let  $A = \{k: |z_k| > c\}$  and |A| its cardinality. By Cauchy's inequality

$$c\delta|A| \leq \sum_{A} \delta|z_{k}| \leq (\delta|A|)^{1/2}K^{1/2},$$

and therefore  $\delta |A| \leq Kc^{-2}$ ,

$$\underset{A}{\Sigma} \delta |\widetilde{z}_{k}| \leq \underset{A}{\Sigma} \delta |z_{k}| \leq Kc^{-1}.$$

Since  $|\tilde{z}_k| \le |z_k|$ 

$$||\phi - \tilde{\phi}||_{F}^{2} \le (\sum_{A} \delta |z_{k} - \tilde{z}_{k}|)^{2} \le \delta |A| \sum_{A} \delta |z_{k} - \tilde{z}_{k}|^{2}$$

$$\le 4\delta |A| K \le 4K^{2}c^{-2}.$$

This proves the first assertion. From the definition (1.8) of L and  $|\tilde{z}_k| \leq |z_k|$ ,

$$\sum_{k=1}^{F} [\delta L(\phi_{k}, y_{k}, z_{k}) - \delta L(\phi_{k}, y_{k}, \tilde{z}_{k})] \\
\geq \frac{1}{2} \sum_{k=1}^{F} \delta [|b_{k}|^{2} - |\tilde{b}_{k}|^{2}] - \sum_{k=1}^{F} \delta (b_{k} z_{k} - \tilde{b}_{k} \tilde{z}_{k})$$

where  $b_k = b(\phi_k, y_k)$ ,  $\tilde{b}_k = b(\tilde{\phi}_k, y_k)$ . Now b(x,y) is bounded and Lipschitz in x. Hence  $|b|^2$  is also Lipschitz in x, and for suitable  $B_1$ 

$$\sum_{k=1}^{F} \delta(|b_k|^2 - |\tilde{b}_k|^2) \ge -B_1 ||\phi - \tilde{\phi}||_F \ge -2B_1 Kc^{-1},$$

$$\sum_{k=1}^{F} \delta b_k (z_k - \tilde{z}_k) \leq B_1 \sum_{A} \delta |z_k - \tilde{z}_k| \leq 2B_1 Kc^{-1}$$

$$\begin{split} \sum_{k=1}^{F} \delta(b_k - \tilde{b}_k) \tilde{z}_k &\leq B_1 | | \phi - \tilde{\phi} | |_F \sum_{k=1}^{F} \delta | \tilde{z}_k | \\ &\leq B_1 \cdot 2Kc^{-1} \cdot T^{1/2} \cdot K^{1/2}. \end{split}$$

In the last step we have used Cauchy's inequality and  $|\tilde{z}_k| \le |z_k|$ . By combining these inequalities we get Lemma 4.3.

Lemma 4.4. Let  $\beta > 0$ . There exist  $N_1, c_1, B$  (depending on T and  $\beta$ ) and  $L_1$ , such that

$$V_{\tilde{N}}^{c}(0,x;\tilde{T}) \leq V_{N}(0,x;T) + Bc^{-1} + L_{1}\beta T$$

if 
$$c \ge c_1$$
,  $N_1 \le N < \tilde{N}$ ,  $\tilde{T} = \tilde{N}\delta$ ,  $\tilde{T} - T \ge \beta T$ .

Proof. By (1.8) given  $K_1$  there exists K such that

$$\sum_{k=1}^{F} \delta L(\phi_k, y_k, z_k) \leq K_1 \quad \text{implies} \quad \sum_{k=1}^{K} \delta |z_k|^2 \leq K.$$

Let  $K_1 > V_N(0,x;T)$ , and consider any strategy  $\Delta$  for the game with N steps (2N moves) such that for any open loop  $y^N = (y_1, \dots, y_N)$ 

$$\sum_{k=1}^{F} \delta L(\phi_k, y_k, z_k) = \pi_{\infty}(0, x; y^N, \Delta) \leq K_1.$$

As before F is the step at which exit occurs (or F = N). We must have  $\phi_{F+1} \notin D$  even in case F = N, since otherwise  $\pi_{\infty} = \infty$ . For the game with  $\tilde{N}$  steps we define a strategy  $\tilde{\Delta}$  with  $|\tilde{\Delta}| \le c$  as follows. For  $1 \le k \le F$ , let  $\tilde{\Delta}^k = \pi_N \circ \Delta^k$  be defined by truncation. If  $\tilde{\phi}_{F+1} \notin D$ , the new game stops after  $\tilde{F} \le F$  steps. Suppose that  $\tilde{\phi}_{F+1} \in D$ . Since  $\phi_{F+1} \notin D$ , by Lemma 4.3

$$\operatorname{dist}(\tilde{\phi}_{F+1}, \partial D) \leq ||\tilde{\phi} - \phi||_{F} \leq 2Kc^{-1}.$$

As in the proof of Lemma 4.2 let A be the  $\alpha$ -neighborhood of  $\partial D$ , where  $\alpha < \beta T$  is sufficiently small. Then  $\tilde{\phi}_{F+1} \in A$  for large enough c. For  $k = F+1, \ldots, \tilde{N}$ , let  $\tilde{z}_k = \underline{z}(\tilde{\phi}_{F+1})$ , where  $\underline{z}(x)$  is defined as in the proof of Lemma 4.2. This defines the strategy  $\tilde{\Delta}$ . For large enough  $N_1$ ,  $\tilde{\phi}_{F+1} \notin D$  where  $\delta(\tilde{F}-F) < \beta T$ . For each open loop  $y^N$  we then have

$$\pi_{\infty}(0,x;y^{N},\tilde{\Delta}) = \sum_{k=1}^{F} \delta L(\tilde{\phi}_{k},y_{k},\tilde{z}_{k}) + \sum_{k=F+1}^{\tilde{F}} \delta L(\tilde{\phi}_{k},y_{k},\underline{z}(\tilde{\phi}_{F+1})).$$

Let  $L_1$  be as in the proof of Lemma 4.2. By Lemma 4.3

$$\pi_{\infty}(0,x;y^{N},\tilde{\Delta}) \leq \sum_{k=1}^{F} \delta L(\phi_{k},y_{k},z_{k}) + Bc^{-1} + L_{1}\beta T$$

$$= \pi_{\infty}(0,x;y^{N},\Delta) + Bc^{-1} + L_{1}\beta T.$$

Hence,

$$V_{N}^{C}(0,x;\tilde{T}) \leq \sup_{y^{N}} \pi_{\infty}(0,x;y^{N},\tilde{\Delta}) \leq$$

$$\sup_{y^{N}} \pi_{\infty}(0,x;y^{N},\Delta) + Bc^{-1} + L_{1}\beta T.$$

Since the inf over  $\Delta$  of the first term on the right side is  $V_N(0,x;T)$ , this gives Lemma 4.4.

By exactly the same change of time scale argument as for Lemma 4.1:

<u>Lemma 4.5</u>. <u>Let</u>  $T < \tilde{T}$ . <u>Then there exist</u>  $R_1, N_1, c^*$  <u>such that</u>

$$|V_N^C(0,x;T) - V_N^C(0,x;\tilde{T})| \le R_1(\tilde{T}-T)$$

for all  $N \ge N_1$ ,  $c \ge c^*$ .

Theorem 4.2.  $V_N(0,x;T) \rightarrow I(0,x;T)$  as  $N \rightarrow \infty$ .

<u>Proof.</u> For each M and c > c(M) Theorem 3.3 implies

$$I_{M}(0,x;T) = \lim_{N\to\infty} W_{N}(0,x;T) \leq \liminf_{N\to\infty} V_{N}^{C}(0,x;T).$$

Let  $\beta > 0$ . Choose  $\tilde{N}$ ,  $\tilde{T} = \tilde{N}\delta$  as in Lemma 4.4 such that  $\beta T \leq \tilde{T} - T \leq 2\beta T$ . For  $c \geq c_1$ ,  $N \geq N_1$ 

$$V_{\tilde{N}}^{c}(0,x;\tilde{T}) \leq V_{N}(0,x;T) + Bc^{-1} + L_{1}\beta T.$$

By Lemma 4.5, for  $c \ge c^*$ 

$$|V_{\widetilde{N}}^{c}(0,x;\widetilde{T}) - V_{\widetilde{N}}^{c}(0,x;T)| \leq R_{1}(\widetilde{T}-T) \leq 2\beta TR_{1}.$$

Therefore,

$$I_{M}(0,x;T) \leq \lim_{N\to\infty} \inf V_{N}(0,x;T) + Bc^{-1} + \beta T(L_{1}+2R_{1}).$$

However, c is arbitrarily large and  $\beta$  arbitrarily small. From (3.16) we then have

$$I(0,x;T) \leq \liminf_{N\to\infty} V_N(0,x;T).$$

To prove the opposite inequality, let  $0<\beta<\frac{1}{2}$ . For N large we can choose  $\hat{T}=\delta\hat{N}$  as in Lemma 4.2 with  $\beta T \leq T-\hat{T} \leq 2\beta T$ . Then

$$V_N(0,x;T) \leq V_N^c(0,x;T) \leq W_N(0,x;\hat{T}) + L_1(T-\hat{T}).$$

By Lemma 4.1

$$|W_{\hat{N}}(0,x;\hat{T}) - W_{\hat{N}}(0,x;T)| \le R_1(T-\hat{T})$$

provided  $\delta = TN^{-1}$  is small enough that  $\hat{N} \ge N_1$ . Since  $T - \hat{T} \le 2\beta T$ , Theorem 3.3 implies

$$\limsup_{N \to \infty} V_{N}(0,x;T) \leq \lim_{N \to \infty} W_{\widehat{N}}(0,x;T) + 2\beta T(R_{1}+L_{1})$$

$$= I_{M}(0,x;T) + 2\beta T(R_{1}+L_{1})$$

for  $c \ge c(M)$ . Since  $\beta$  is arbitrarily small and  $I_M \le I$ ,

$$\lim_{N\to\infty}\sup V_N(0,x;T) \leq I(0,x;T).$$

This proves Theorem 4.2.

Theorem 4.2 justifies calling I(0,x;T) the lower value.

Concluding remarks. It should be possible to show that I(s,x;T) = I(0,x;T-s) satisfies for almost all (s,x) the Isaacs equation, which is the first order equation obtained from (2.7') when  $\varepsilon = 0$ . However, we have not done so. One could perhaps show that  $I(\cdot,\cdot;T)$  is Lipschitz for  $s \le T' < T$ , and then use an argument like the proof of [F2, p. 1005].

The lower value I(0,x;T) is a nonincreasing function of T. Let

$$I^*(x) = \lim_{T \to \infty} I(0,x;T).$$

It would be interesting to investigate various properties of  $I^*(x)$ . For instance, is  $I(0,x;T) = I^*(x)$  for some finite T? That kind of result is suggested by examples treated by the method of characteristics for the Isaacs equation.

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The problem is to control the drift of a Markov diffusion process in a way that the probability that the process exits from a given region D during a given finite time interval is minimum. An asymptotic formula for the minimum exit probability when the process is nearly deterministic is given. This formula involves the lower value of an associated differential game. It is related to a result of Ventsel and Freidlin for nearly deterministic, uncontrolled diffusions.	

